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Drone Aided Machine-Learning Tool for Post-Earthquake Bridge Damage Reconnaissance

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Abstract

After a high-intensity seismic event, inspections of structural damages need to be carried out as soon as possible in order to optimize the emergency management, as well as improving the recovery time. In the current practice, damage inspections are performed by an experienced engineer, who physically inspect the structures. This way of doing not only requires a significant amount of time and high skilled human resources, but also raises the concern about the inspector's safety.

A promising alternative is represented using new technologies, such as drones and artificial intelligence, which can perform part of the damage classification task. In fact, drones can safely access high hazard components of the structures: for instance, bridge piers or abutments, and perform the reconnaissance by using high-resolution cameras. Furthermore, images can be automatically processed by machine learning algorithms, and damages detected.

In this paper, the possibility of applying such technologies for inspecting New Zealand bridges is explored. Firstly, a machine-learning model for damage detection by performing image analysis is presented. Specifically, the algorithm was trained to recognize cracks in concrete members. A sensitivity analysis was carried out to evaluate the algorithm accuracy by using database images. Depending on the confidence level desired,i.e. by allowing a manual classification where the alghortim confidence is below a specific tolerance, the accuracy was found reaching up to 84.7%.

In the second part, the model is applied to detect the damage observed on the Anzac Bridge (GPS coordinates -43.500865, 172.701138) in Christchurch by performing a drone reconnaissance. Reults show that the accuracy of the damage detection was equal to 88% and 63% for cracking and spalling, respectively

Keywords: Post-earthquake reconnaissance, drone inspection, machine-learning

1. INTRODUCTION

Bridges are one of the critical elements in civil infrastructures which are constantly exposed to the environment. Hence they require a level of maintenance which is higher than traditional buildings to ensure their safety and operability. Traditional inspection procedures are carried out on-site by expert engineers, and therefore these tasks are often labour-intensive and time-consuming. Furthermore, some bridges might be difficult to access (Figure 1(a)) which might raise a concern on the inspector safety. In order to improve the current practice, this project aims to develop a drone-aided machine-learning (ML) tool that can automatically detect the state of damage in a bridge. At this stage, the scope of the study is limited to the detection of cracking and spalling in reinforced concrete (RC) elements. Before presenting the proposed tool in detail, the fundamental knowledge of the key components of this study are presented in order: 1) available machine-learning algorithms, 2) typical crack locations in RC bridges, 3) current bridge inspection procedures and 4) the use of drones in civil engineering inspections.

(a) (b)

Fig. 1 – (a) Traditional bridge inspection with accessing difficulties by [1]; (b) Drone-aided inspection on the Anzac Drive Bridge

1.1.Machine-learning Algorithm

Machine Learning (ML) is a branch of Artificial Intelligence (A.I.) that automates the analysing process. As an overview, AI refers to an artificial creation of human-like intelligence that could process, learn and plan certain languages. Figure 2 shows a Venn diagram that demonstrates the evolution in the ML field.

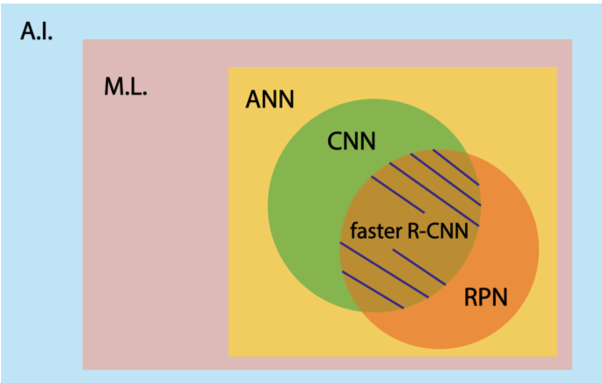

Fig. 2 – The Venn diagram of the evolution in ML

Traditionally, pre-trained machine-learning algorithms can learn from data, identify patterns and make decisions with minimal human intervention. Among the different ML algorithms, Artificial Neural Network (ANN) is a computing system that was inspired by biological neural networks [2]. An ANN is functioning based on collecting signals from connected units called artificial neurons. Similar to the neurons in human brains, signals are transmitted from the input layer through many hidden layers to the output layer. Within the transitions, a coefficient called “weight” has been used to adjust the strength of the signal. Ideally, any errors can be minimised by choosing the optimised “loss function”.

Among many proposed ANNs, convolutional neural network (CNN) has been implemented to countless computer vision tasks. Compared to traditional ANN approaches, CNN can successfully capture the spatial and temporal dependencies in an image. The architecture of CNNs performs a better fitting to the image dataset due to the reduction in the number of parameters and reusability of weights. Of these CNNs, VGG16 is one of the most appropriate for image classification and detection [3].

Having combined the concepts above, a faster R-CNN has been used as a base model to develop the damage classification algorithm. A faster R-CNN involves two processes which are a traditional CNN and a Regional Proposal Network (RPN). In this project, pre-trained faster R-CNN [4] has been used to perform damage detection.

1.2.Typical damage locations in RC New Zealand Bridges

The most common type of bridge in New Zealand for low/medium spans (5-12 m) is the beam or girder bridge [5]. This type of bridge is often made of reinforced concrete, which is the cheapest option amongst the others. By 2009, there were 2,174 rail bridges and over 15,600 road bridges in New Zealand [6]. The total number of bridges would have increased over these ten years. Engineers should be prepared to inspect a large number of bridges that are currently under different conditions.

Concrete cracks form under high compression and tensile forces. The location where these cracks arise becomes the critical area where the reinforcement becomes exposed to the air. Therefore, the reinforcement in that location is at a higher risk of corrosion. Not just cracks, but phenomena such as delamination and spalling, are typical indicators of corroded areas [7]. When corrosion occurs, the capacity of the structural member is reduced.

Generally, cracks are likely to occur in the negative moment regions around the intermediate columns. The cracking densities and sizes depend on the bridge span lengths, deck thickness, beam span-to-depth ratio and girder properties, etc.

It is evident that predominant form of deck cracking is transverse cracking for most of the bridges, and transverse cracks could accelerate corrosions of reinforcing bars [8]. Although the internal corrosions of steel bars are hard to detect in the preliminary inspection, with the transverse cracks labelled on the bridge, engineers can predict the locations or corroded steel bars.

1.3. Current inspection procedures

The causes and mechanisms of bridge failures can be categorised as natural phenomena and manmade factors [9]. Natural causes include earthquake, wind, cyclone, scour, landslide, etc. Manmade factors are mainly: design and construction errors, overloading, collision, fire and lack of inspection/maintenance. Therefore, regular inspections are crucial to maintaining the safety of the structure.

Nowadays, bridge inspection methods include visual inspection, acoustical techniques, infrared/thermal imaging inspection, coring and chipping, ground-penetrating radar and half-cell potential test. The last detection method specifically assesses the voltage between the rebar in the concrete and an electrode placed on the concrete’s surface so that the amount of corrosion can be detected [10].

However, every bridge inspection starts from a preliminary visual inspection. As mentioned above, these preliminary assessments are carried out by experienced structural engineers which can be time-consuming and expensive [5].

In this paper, an alternative to the traditional visual inspection is proposed. The alternative consists of a survey performed by a drone, which automatically classifies the damage typologies through an ML algorithm.

1.4. Drone-aided inspection

Nowadays, drone inspections are getting popular in monitoring structural health by scanning certain areas on the surface. Traditional visual inspections have physical limitations since engineers cannot access most of the inspecting points without external supporting machinery (i.e. scissor lifts, spider cranes). By contrast, drones can fly up to an optimal height where the targeting point lines up with the camera so that potential risks for inspectors are decreased. High-resolution images even videos could then be collected by the camera. The time required for inspection can be reduced significantly, as well as the learning cost of operating a drone for inspections. Remotely controlled drones have advanced sensors that support technologies including infrared thermography, data delivering, real-time tracking and terrain recognition, etc. The detailed drone inspection method will be discussed in 3.1 Site Visit.

2. Materials and Methodology

2.1.Bridge Damage Dataset

A dataset was produced as part of the project work. It consisted of a total of 330 medium-high resolution images selected from the Canterbury Bridge Database (courtesy of Alessandro Palermo) and major search engines. Each image (Figure 3) contained either cracking or spalling damages on RC bridges. Damages were annotated within the bounding boxes and labelled according to their typologies.

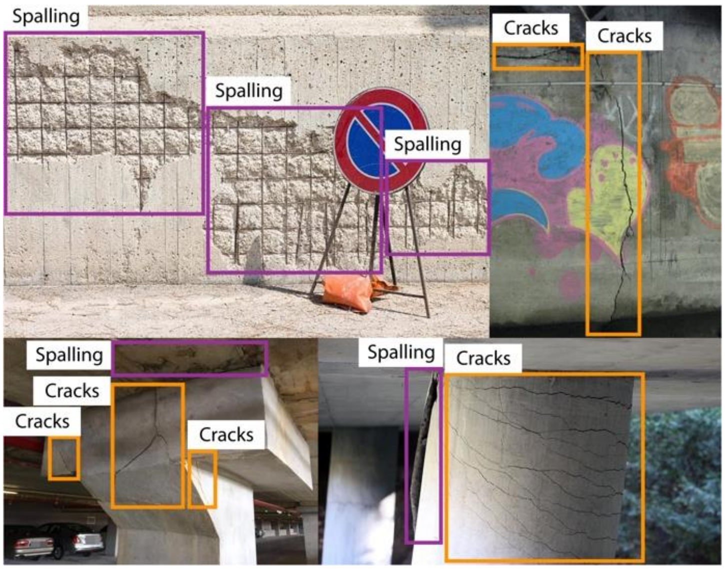

Fig. 3 – Demonstration of image database with labelled damages

During the damage classification, two damage types were defined: cracking and spalling. One reason for selecting these two classes for experimentation was that these are the two major types of damages directly caused by the seismic events. Another reason is that both of these damage types have specific traits in the visual level and can be easily recognised by humans. Hence, it is reasonable to assume that the machine could learn to do the same as the ANN works similar to a human brain.

The exclusion of corrosion in the damage class was due to its difficulty of being visually diagnosed. Without the help of scientific machinery, most corrosion damages were found due to the spalling of cover concrete. Figure 3 illustrates examples of each of these damage classes. The number of annotations for each damage type used for training and testing is summarised in Table 1.

Table 1 – Statistics of detected damages in the training database

Number of Annotations		
Classes	Training	Testing
Cracking	533	47
Spalling	207	27

2.2.Damage Detection Framework

The proposed method has been composed of the training process and the damage detection process. The training process referred to the development of a machine-learning tool that can automatically detect the presence of damages on RC bridges. The damage detection process involved a proposed inspection method and the implementation of the developed ML tool. Figure 4 illustrates the flowchart of the proposed procedure from images collecting to results generation where VGG16 and faster R-CNN are applied.

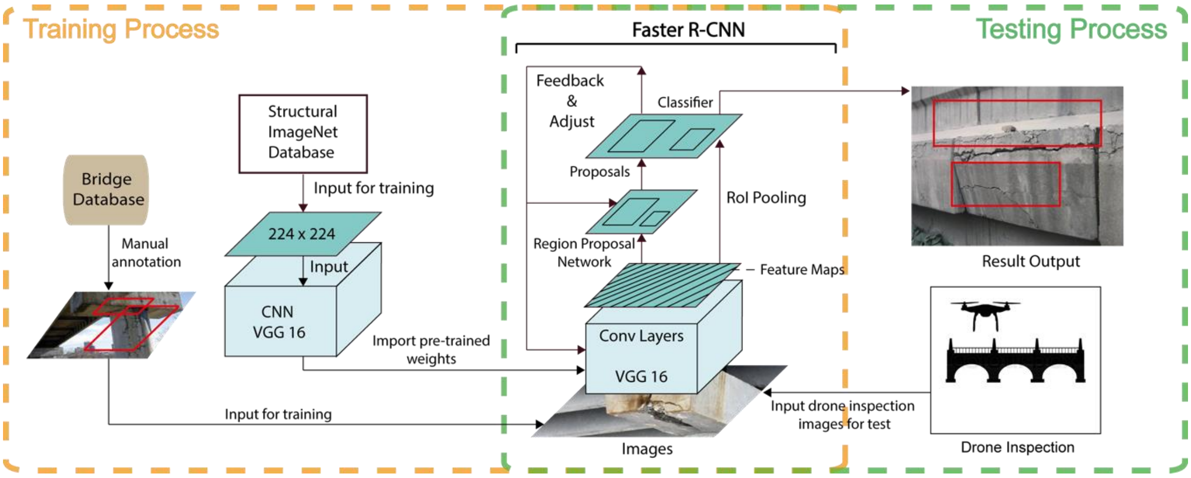

Fig. 4 – The flowchart of the training and testing process with faster R-CNN implemented

2.2.1. Training VGG16 Net

The ultimate goal of the training process is to develop an ML algorithm that works on images of any size. Using a faster R-CNN framework was considered to be the best approach to complete such a task. However, the quantity and quality of the datasets are critical factors in the training process. Since it is challenging to acquire an open-sourced database regarding bridge damages, a database named Structural ImageNet available in [11] were used. The Structural ImageNet contained a total of 5,911 images regarding damaged and undamaged structures. These images were consistent, with a size of 224 × 224 pixels as they were specifically converted to be compatible with typical CNNs like the VGG16 Net used in this task.

The labelled images from the database were divided into a training set and a validation set with a proportion of 80% and 20% respectively. During the training, the VGG16 Net can learn key features extracted from the images inside the training set. The images have been used to validate the performance of the algorithm after each epoch of training (where one epoch is defined as the entire training set had been used once for training the detection model). A weight file was generated at the completion of training. Combining the VGG16 architecture with the weight file, a classification task can be performed to check whether a damaged object is presented inside an input image.

2.2.2. Faster R-CNN

To further improve the capability of the algorithm, a VGG16-based faster R-CNN object detection framework was established and the previously obtained weights were inherited. The framework was then trained from the produced Bridge Damage Dataset. During each training cycle, the convolutional layers converted the image into special features called the feature map. The Region Proposal Network (RPN) then predicted multiple regions that the objects could locate in. The Region of Interest (ROI) pooling was used to extract certain features corresponding to the proposed regions from the feature map. The classifier then decided whether the particular object class was presented in the proposed regions. In the end, the proposed regions and classified objects were compared to the annotation of the original image, the weights of VGG16 and parameters inside the RPN were then adjusted accordingly.

2.2.3. Bridge Inspection Method

The ideal flight route of the drone would weave between the piers beneath the deck. This ensures that the flight path has adequate angles for the drone to take photos covering the outside surface of the entire bridge. More attention should be paid to locations that are more susceptible to damages, and extra photos should be taken from different angles. For a typical RC beam bridges, the damages mainly appear at the bottom and end of decks, top of bridge piers and abutments, and connections between deck and piers.

2.2.4. Damage Detection

The obtained photos from the field can then be input into the completed ML algorithm. The algorithm can automatically detect cracking and spalling damages from the images.

2.3. Algorithm Implementation

2.3.1. Hardware

All work conducted under this project was performed on a Windows 10 machine with one Intel Xeon CPU E3-1230 processor. All the training processes were boosted by a NVIDIA Geforce GTX 650 graphic card. The time required for training the VGG16 network for 100 epochs was 4.2 hours. The time required for training the faster R-CNN network with 10,000 iterations was 27 hours.

2.3.2. Software and Codes

TensorFlow deep-learning application program interface (API) [12] was used for experimenting with the training and testing of VGG16 network. Open-sourced python package [13] was modified and used to conduct training and testing of faster R-CNN object detection method.

2.4.Training Outcome

After training the VGG16 network with 60 epochs the algorithm reached the accuracy of 78.5% base on the validation dataset. Figure 5 shows the change in training and validation accuracy against the number of epochs. It can be seen that accuracy rapidily increases within the first 10 epochs before becoming more stable. This indicates that the machine started to learn about the features and patterns of the input training set and started to reflect its performance optimization on the validation set. After 10 epochs of training, the training accuracy converges to the maximum, which is close to 1, as the machine has seen and recognise all images in the training set. On the contrary, the validation accuracy started to oscillate due to the potential of the loss function over-fitting the training set.

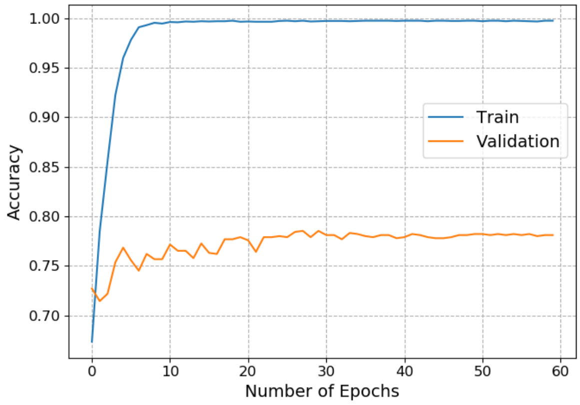

Fig. 5 – Training and validation accuracy changes responding to the increased number of epochs

Further investigation has been conducted to understand the behaviour of the algorithm further in-depth. By analysing the outputs of this image classification task, which are two numbers for each classified image. These two numbers add up to 1 and represent the probability of being classified as each category. In other words, these two numbers represent the confidence level of the machine to its decision. In order to further improve the performance of the algorithm, a confident threshold is introduced to reduce the chance of failure. The confident threshold represents the absolute difference between the probability of the image being undamaged or damaged. Images can be flagged for manual classification, if the confidence threshold exceeds a certain value, as classification of the image is less certain.

Figure 6 indicates the change in accuracy and percentage of flagged images as the confidence threshold increases, assuming that the accuracy of manual classification is 100%. Both trendlines incline slowly along with the increasing in confidence threshold. It appears that the algorithm maintained a high confidence level regarding its decisions regardless of its correctness.

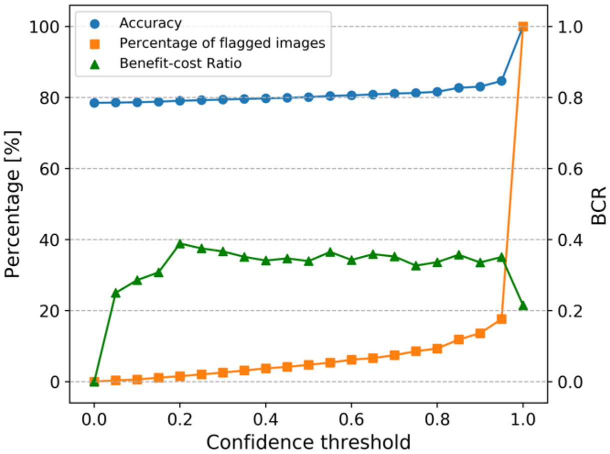

Fig. 6 – The increasing trend of accuracy (%) with the corresponding confidence threshold

To find the optimal point between the increase in accuracy and the number of images flagged for manual classification, the benefit-cost ratio (BCR) has been used as the key measurement. The BCR was calculated as the gain in accuracy over the proportion of flagged images shown in Equation 1. The change in BCR was plotted against the change in confidence threshold, which is shown in Figure 6.

$$BCR = \frac{\text{Change in accuracy}}{\text{Percent of flagged images}} \tag{1}$$

It is observed that the BCRs are less than 1.0 at all levels of confidence threshold, which indicates that the costs outweigh the benefits. In this specific case, it is acceptable to pay more labour to exchange for benefits as the consequences of missing potential damages could be much higher than the cost of labour. The trend indicates that the confidence threshold should be set to 20% as the benefit over cost is maximised. The accuracy can be improved up to approximately 84.6% with manually classifying 17.6% of images.

3. CASE STUDY

3.1.Site Visit

To test the feasibility of the proposed inspection procedure and the performance of the developed ML algorithm, the Anzac Drive bridge has been selected to be the case study subject.

Fig. 7 – Elevation view drawings of the Anzac Drive Bridge

The Anzac Drive Bridge was initially constructed in 2000 (shown in Figure 7). It is a four-lane concrete beam bridge located about 6 km north-east of central Christchurch [14]. The bridge has three 18 m simply supported decks. The piers consist of four reinforced concrete columns, designed as portal frames. Inspections were conducted after both the 2010 Darfield Earthquake and the 2011 Christchurch Earthquake. According to the inspection log from the Canterbury Bridge Database, significant structural damages including cracks, concrete spalling and abutment rotation, were observed. The bridge has been repaired after the 2011 Christchurch Earthquake.

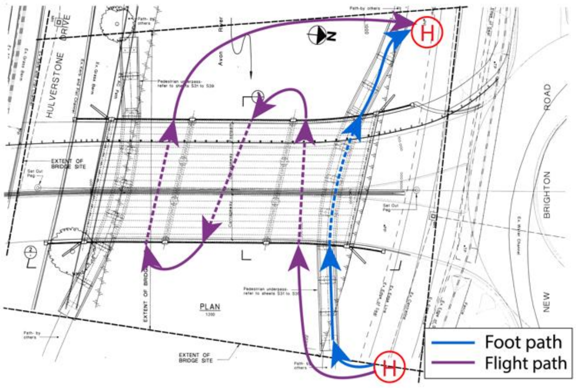

Fig. 8 – Drone inspection flight plan

As shown in Figure 8, the purple line indicates the flight path of the drone and the blue line represents the inspectors' walking path. By following the proposed inspection method, a drone was controlled to weave between the piers while the inspectors were walking through the pedestrian underpass. The elevation view of the deck and all faces of bridge columns were covered, and photos were obtained. The entire inspection was completed within 20 minutes.

3.2. Test and results

The obtained images taken by the drone have a default size of 5472 × 3648 pixels. It took the algorithm approximate 5.1 seconds to generate 300 regional proposals and classify damages.

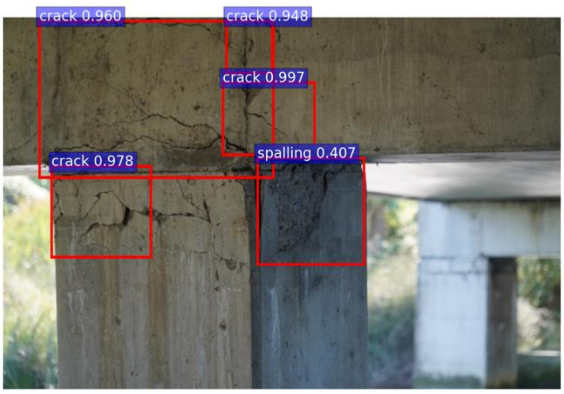

Fig. 9 – An example of effective damage detection

Figure 9 is one example of the algorithm output and the spotted damages at one connection of the portal frames were identified. The red bounding box indicates that a type of damage was detected inside the box. The corresponding damage type with its confidence level (CL) is shown in the blue box attached to the bound of the boxes. The cracks and concrete spalling were successfully identified except part of a long crack was observed outside the bounding box. This could be due to the RPN failing to propose precise regions or the

VGG net only recognising part of the cracking pattern. It is reasonable to expect that the algorithm is more confident about the identified cracks (CL > 0.90) and less confident about the identified spalling (CL < 0.5), as the number of annotated cracking damages used for training was twice as many as the spalling damages.

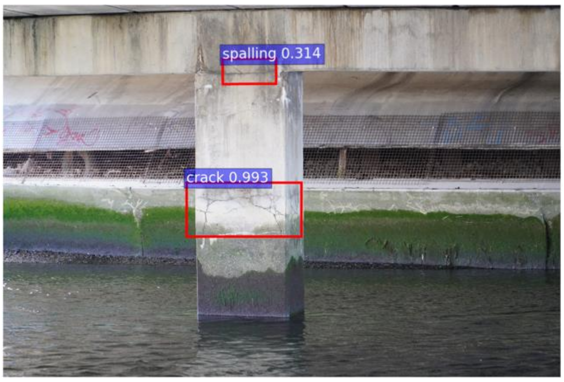

Fig. 10 – An example of an incorrect damage detection at the beam-column interface

Figure 10 is another example of the output results. The flexural cracks on the bridge column were identified with a high CL. However, the algorithm mistakenly classified the crack at the top of the column as spalling. This potentially indicates that the algorithm tended to categorise the spalling damage based on the colour variation inside of the texture variation within the region.

The accuracy of multiple object classification is hard to be quantified as the categorising correctness and bounding precision are both important contributing factors. To simplify the performance measurement, locations which contained identified damages within were counted. By inputting the 25 images obtained from the field, the algorithm identified 34 locations with the presence of damage. Twenty-eight cracking damages and five spalling damages were correctly identified. However, the algorithm failed to point out three cracking and three spalling locations. In addition, one cracking damage was mistaken as spalling damage. The results were summarised into a normalised confusion matrix in Figure 11 shown below.

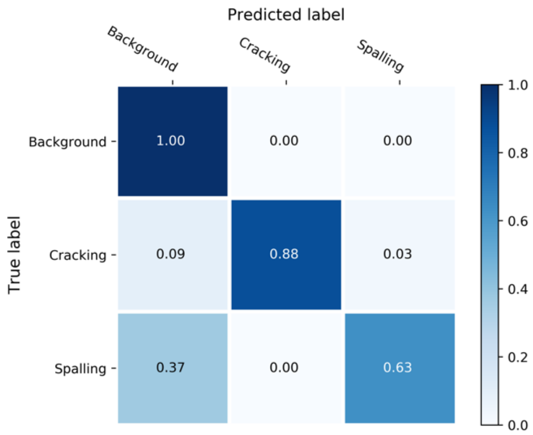

Fig. 11 – The normalised confusion matrix of the tested result generated by the algorithm

In this normalised confusion matrix, a background category, which represents the regions without any damages was introduced. The value in the central box indicates that 88% of actual cracks were correctly predicted. Similarly, the value in the lower right corner indicates that 63% of spalling damages were identified.

Overall, the damage detection algorithm had an accuracy of 82.5%. It is fair to say that the algorithm performed well on the cracking detection but not ideal for spalling recognition. This could be the result of the difference in the number of damage annotations used for training. It is noteworthy that the quantified performance measurements only represent how well the algorithm performed on this specific task, as the number of samples was not adequate to represent the population.

Further adjustment can be made to improve the performance of the algorithm in general. The most effective approach would be increasing the number of images used for training. It is more likely for the machine to figure out the key features of a class if more images with the common features are provided. In addition, with more images with different crack shapes so that the machine can recognise. Another approach is fine-tuning the training set. Some images inside the training set might have features that would mislead the algorithm. For example, if the annotations of many spalling damages contain features like high contrast or the same colour, the machine could misunderstand these as the key features that should be referred to. To avoid this, training images with specific features like the changes in the surface texture should be targeted.

4. CONCLUSION AND RECOMMENDATIONS

This paper proposed an idea for using drones and an ML tool to perform post-earthquake inspections and damage detection tasks on reinforced concrete bridges. A complete ML algorithm was developed to detect the presence of cracking and spalling damages on the bridge surface. New inspection procedures were presented and validated by carrying out a case study. The results determined an overall accuracy of 82.5%. The behaviour of the algorithm has been analysed and the results indicated that the machine can be effectively trained to perform damage detection tasks.

As the consequence of failing to identify the presence of damages could be severe, the proposed procedure is not ready for imminent application. However, it represents a promising possibility for the future. Strategies to deal with the uncertainty and to minimise the risk should be developed.

5. FUTURE DEVELOPMENT

In this project, the proposed procedure is limited to RC bridges because it is the most common typology in New Zealand. However, in the future, the procedure can be to other bridge typologies. Having expanded the database, more images with diverse damage types could use for training and testing so that damage can be detected on bridges made of timber and steel. Meanwhile, challenges may arise when the bridge materials altered from reinforced concrete to other types. For example, steel bridges are often suffering from safety issues due to metal failures. Unlike RC cracks, metal failures including fatigue, cavitation and corrosion are hard to be observed from the surface. Therefore, the detection process will need to be further developed to be able to distinguish confined details.

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